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Artificial intelligence techniques for sizing photovoltaic systems: A review

A. Mellit [a,1], S.A. Kalogirou [b,*], L. Hontoria [c], S. Shaari [d]

[a] Department of Electronics, Faculty of Science Engineering, LAMEL Laboratory, Jijel University, P.O. Box 98, Oulad Aissa, Jijel 18000, Algeria
[b] Department of Mechanical Engineering and Materials Science and Engineering, Cyprus University of Technology, P.O. Box 50329, Limassol 3603, Cyprus
[c] Grupo Investigación y Desarrollo en Energía Solar y Automática, Dpto. de Electrónica, E.P.S. Jaén, Universidad de Jaén, Avda., Madrid, 35, 23071 Jaén, Spain
[d] Faculty of Applied Sciences, Universiti Teknologi MARA 40450 Shah Alam, Selangor, Malaysia

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Abstract

Artificial intelligence (AI) techniques are becoming useful as alternate approaches to conventional techniques or as components of integrated systems. They have been used to solve complicated practical problems in various areas and are becoming more and more popular nowadays. AI-techniques have the following features: can learn from examples; are fault tolerant in the sense that they are able to handle noisy and incomplete data; are able to deal with non-linear problems; and once trained can perform prediction and generalization at high speed. AI-based systems are being developed and deployed worldwide in a myriad of applications, mainly because of their symbolic reasoning, flexibility and explanation capabilities. AI have been used and applied in different sectors, such as engineering, economics, medicine, military, marine, etc. They have also been applied for modeling, identification, optimization, prediction, forecasting, and control of complex systems. The main objective of this paper is to present an overview of the AI-techniques for sizing photovoltaic (PV) systems: stand-alone PVs, grid-connected PV systems, PV-wind hybrid systems, etc. Published literature presented in this paper show the potential of AI as a design tool for the optimal sizing of PV systems. Additionally, the advantage of using an AI-based sizing of PV systems is that it provides good optimization, especially in isolated areas, where the weather data are not always available.

Keywords: Artificial intelligence; Neural network; Fuzzy logic; Genetic algorithm; Wavelet; Hybrid system; Photovoltaic systems; Sizing

Contents

Abbreviations: AI, artificial intelligence; ANN, artificial neural network; DRNN, dynamic recurrent neural network; DWT, discrete wavelets transform; ES, expert system; FIR, finite impulse response; FL, fuzzy logic; FLC, fuzzy logic control; GA, genetic algorithm; HPV, hybrid PV system; HS, hybrid system; IDWT, inverse DWT; IES, Instituto de Energia of Madrid; IIR, infinite impulse response filter; LLP, loss of load probability; LM, Levenberg–Marquardt; LPSP, the loss of power supply probability; MLP, multi-layer perceptron; MPPT, maximum power point tracker; PV, photovoltaic; PVGCS, PV grid-connected system; RBF, radial basis function; RE, renewable energy; RMSE, root mean square error; RNN, recurrent neural network; SAPV, stand-alone PV-system; SOC, battery state of charge; WG, wind-generator; WTG, wind turbine generators.

* Corresponding author. Tel.: +357 2500 2621; fax: +357 2500 2769.
E-mail address: skalogir@spidernet.com.cy (S.A. Kalogirou).

[1] Junior associate member at International Center Theoretical Physics ICTP, Trieste Italy (www.ictp.it).

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Nomenclature

A_{pv}	PV-array area (m^2)
Alt	altitude (m)
Bi	inverter capacity
C_A	capacity of the generator
C_S	capacity of the battery
C_{SEC}	costs that depend on the optimal strategy (€)
C_{SOP}, C_{AOP}	optimal sizing coefficient
C_{TOT}	total cost throughout the life of the system (€)
C_u	useful capacity (Wh)
f, u	sizing coefficient obtained by using hybrid method
f_p,u_p	predicted sizing coefficient obtained by using hybrid method
H	irradiation (Wh/m^2/day)
K_{PV}, K_B	new optimal sizing coefficient of PV-system
K_t	clearness index
Lat	latitude (°)
Lon	longitude (°)
Ngen_main	number of main generation
Ngen_sec	number of second generation
Nm	population of the GA
Nsec	Number of vectors of secondary algorithm
Pl	power demand
Sp	generating power (PV)
T	temperature (°C)
w_{ij}	weight of the neuron
W	wind speed (m/s)
Wp	generating power (wind)

1. Introduction

The term artificial intelligence (AI) has been applied to computer systems and programs that can perform tasks more complex than straightforward programming, although still far from the realm of actual thought. AI consists of many branches, such as, expert systems (ES), artificial neural networks (ANN), genetic algorithms (GA) and fuzzy logic (FL) and various hybrid systems, which are combinations of two or more of the branches mentioned previously [1]. AI technologies have a natural synergism that can be exploited to produce powerful computing systems. A theme that can be found in these alternatives is the attempt to make up for deficiencies in the conventional approaches. In some cases, the goal is to produce better, more efficient and effective computing systems. Sometimes this requires adding features associated with human intelligence such as learning and the ability to interpolate from current knowledge. The appropriate use of intelligent technologies leads to useful systems with improved performance or other characteristics that cannot be achieved through traditional methods [2]. AI-techniques have been used in several domains and applications [3–8].

Renewable energy (RE) resources have enormous potential and can meet the present world energy demand. They can enhance diversity in energy supply markets, secure long-term sustainable energy supply, and reduce local and global atmospheric emissions. They can also provide commercially attractive options to meet specific needs for energy services (particularly in developing countries and rural areas), and offer possibilities for local manufacturing of equipment [9].

In addition, the use of RE resources have been charted specifically in many of the roadmaps of the developed countries. One of the most promising RE technologies is photovoltaic (PV) technology. PV systems are popularly configured as stand-alone, grid-connected, and hybrid systems. They are developing rapidly in the world, both in the developed and developing nations.

The performance of the PV system depends upon several factors, especially the meteorological conditions such as solar radiation, ambient temperature and wind speed. In order to size a PV system so that it can work properly, efficiently and economically to meet the desired load requirements under the local meteorological conditions, the characteristic performance of each component in the PV system is required. Normally, the information provided about the PV module and other components from the manufacturers is used for sizing the PV system by a rough estimation of the system output based on average values of daily meteorological data inputs [10].

In any PV system, sizing represents an important part of PV systems design, i.e., the optimal selection of the number of solar

cell panels, the size of the storage battery and the size of wind-generator to be used for certain hybrid applications. At a particular site it is an important economical task for electrification of villages in rural areas, telecommunications, refrigeration, water pumping, water heating, etc. Besides being an economic waste, an oversized system can also adversely affect further utilization of solar cells and the pollution-free PV energy. Undoubtedly, at the present stage of development of the PV technology, the major impediment to a wider market penetration, as noted by Haas [11], is the high investment costs of the PV systems. However, estimation of the sizing parameters such as the PV-array area, useful capacity of batteries and wind-generator (if used in a hybrid system) is very useful to conceive an optimal PV system. Additionally, conceiving an optimal and economic PV systems is very important particularly in isolated sites (Sahara regions, small island archipelagos, remote areas in developing nations, mountainous locations, rural regions, etc.). Hybrid energy systems use different energy resources such as solar and wind energy and diesel gensets. These are an economical option in areas isolated from the grid.

The present paper aims at reviewing the current state of PV systems sizing based on the application of Artificial intelligence (AI) techniques. This is followed by a review of work reported by several authors. This paper also gives a brief introduction of AI-techniques.

2. Artificial intelligence techniques

Artificial intelligence (AI) is a term that in its broadest sense would mean the ability of a machine or artefact to perform similar kinds of functions that characterize human thought [3].

2.1. Artificial neural networks

An ANN is a collection of small individually interconnected processing units. Information is passed through these units along interconnections. An incoming connection has two values associated with it, an input value and a weight. The output of the unit is a function of the summed value. ANN's while implemented on computers are not programmed to perform specific tasks. Instead, they are trained with respect to data sets until they learn the patterns used as inputs. Once they are trained, new patterns may be presented to them for prediction or classification. ANN's can automatically learn to recognize patterns in data from real systems or from physical models, computer programs, or other sources. An ANN can handle many inputs and produce answers that are in a form suitable for designers [1]. ANNs are based on our present understanding of the brain and its associated nervous systems. They use processing elements connected by links of variable weights to form a black box representation of systems [5].

A typical ANN comprises several layers of interconnected neurons, each of which is connected to other neurons in the ensuing layer. Data are presented to the neural network via an input layer, while an output layer holds the response of the network to the input. One or more hidden layers may exist between the input layer and the output layer. All hidden and output neurons process their layer inputs by multiplying each input by its weight, summing the product, and then processing the sum using a non-linear transfer function to generate a result [5].

Neural networks have the potential to provide some of the human characteristics of problem solving that are difficult to simulate using the logical, analytical techniques of expert system or standard software technologies. For example, neural networks can analyze large quantities of data to establish patterns and characteristics in situations where rules are not known and can in many cases make sense of incomplete or noisy data. These capabilities have thus far proven too difficult for traditional symbolic or logic-based approaches [1]. The immediate practical implication of neural computing is its emergence as an alternative or supplement to conventional computing systems and AI-techniques. As an alternative, neural computing can offer the advantage of execution speed, once the network has been trained. The ability to train the system with data sets, rather than having to write programs, may be more cost effective and may be more convenient when changes become necessary. In applications where rules cannot be known, neural networks may be able to represent those rules implicitly as stored connection weights [1].

The greatest advantage of ANNs over other modeling techniques is their capability to model complex, non-linear processes without having to assume the form of the relationship between input and output variables. Learning in ANNs involves adjusting the weights of interconnections. Areas addressed by ANN techniques include pattern matching, combinatorial optimization, data compression, and function optimization. As a developing and promising technology, ANNs have become extremely popular for prediction and forecasting [5,6]. There are several ANN architectures used in literature such as multilayer perceptron (MLP), radial basis function network (RBF) and recurrent neural network (RNN) [12].

2.2. Fuzzy logic

Fuzzy systems (FS) are based on fuzzy set theory and associated techniques pioneered by Lotfi Zadeh [13,14]. A goal of this approach is to mimic the aspect of human cognition that can be called approximate reasoning. Fuzzy systems may be less precise than conventional systems but are more like our everyday experiences as human decision-making. Fuzzy logic (FL) is used mainly in control engineering. It is based on fuzzy logic reasoning which employs linguistic rules in the form of if–then statements. Fuzzy logic and fuzzy control feature a relative simplification of a control methodology description. This allows the application of a 'human language' to describe the problems and their fuzzy solutions. In many control applications, the model of the system is unknown or the input parameters are highly variable and unstable. In such cases, fuzzy controllers can be applied. These are more robust and cheaper than conventional PID controllers. It is also easier to understand and modify fuzzy controller rules, which not only use human operator's strategy but, are expressed in natural linguistic terms [3,4].

Fuzzy logic is very useful in modeling complex and imprecise systems. Under the fuzzy set theory, elements of a fuzzy set are mapped to a universe of membership values using a function–theoretic form belonging to the close interval from 0 to 1. An important step in applying fuzzy methods is the assessment of the membership function of a variable, which parallels the estimation of probability in stochastic models. Membership functions in fuzzy set theory, which are appropriate for modeling the preferences of the decision maker, can be obtained on the basis of actual statistical surveys. Modeling based on fuzzy logic is a simple approach, which operates on an 'if–then' principle, where 'if' is a vector of fuzzy explanatory variables or premises in the form of fuzzy sets with membership functions and 'then' is a consequence also in the form of a fuzzy set [5,6].

2.3. Genetic algorithm

GA's are inspired by the way living organisms are adapted to the harsh realities of life in a hostile world, i.e., by evolution and inheritance. The algorithm imitates in the process the evolution of population by selecting only fit individuals for reproduction. Therefore, a GA is an optimum search technique based on the concepts of natural selection and survival of the fittest. It works with a fixed-size population of possible solutions of a problem, called individuals, which are evolving in time. A GA utilizes three principal genetic operators: selection, crossover, and mutation [3,4].

Genetic algorithms were envisaged by Holland [15] in the 1970s as an algorithmic concept based on a Darwinian-type survival-of-the-fittest strategy with sexual reproduction, where stronger individuals in the population have a higher chance of creating an offspring. A genetic algorithm is implemented as a computerized search and optimization procedure that uses principles of natural genetics and natural selection. The basic approach is to model the possible solutions to the search problem as strings of ones and zeros. Various portions of these bit-strings represent parameters in the search problem. If a problem-solving mechanism can be represented in a reasonably compact form, then GA techniques can be applied using procedures to maintain a population of knowledge structure that represent candidate solutions, and then let that population evolve over time through competition (survival of the fittest and controlled variation). A GA will generally include the three fundamental genetic operations of selection, crossover and mutation. These operations are used to modify the chosen solutions and select the most appropriate offspring to pass on to succeeding generations. GAs consider many points in the search space simultaneously and have been found to provide a rapid convergence to a near optimum solution in many types of problems; in other words, they usually exhibit a reduced chance of converging to local minima. GAs show promise but suffer from the problem of excessive complexity if used on problems that are too large [16].

Genetic algorithm applications are appearing as alternatives to conventional approaches and in some cases are useful where other techniques have been completely unsuccessful. Genetic algorithms are also used with other intelligent technologies such as neural networks, expert systems, and case-based reasoning.

2.4. Wavelet

Wavelet transform (WT) is a novel signal processing technique developed from the Fourier transform and has been widely used to signal processing. The main characteristic of wavelet transform is its time frequency localization. Wavelet transformation (WT) has versatile basis functions, which are selected, based on the type of the signal analyzed. Wavelets have generated a tremendous interest in both theoretical and applied areas, especially over the past few years. The number of researchers applying wavelets is already large and continues to grow, so progress is being made at a rapid pace. In fact, advancements in the area are occurring at such a rate that the very meaning of "wavelet analysis" keeps changing to incorporate new ideas. In a rapidly developing field, overview papers are particularly useful and several good ones concerning wavelets are already available [17].

2.5. Hybrid systems

The increased popularity of hybrid intelligent systems (HIS) in recent years lies to the extensive success of these systems in many real-world complex problems. The main reason for this success seems to be the synergy derived by the computational intelligent components, such as machine learning, fuzzy logic, neural networks and genetic algorithms. Each of these methodologies provides hybrid systems with complementary reasoning and searching methods that allow the use of domain knowledge and empirical data to solve complex problems [18,19]. Hybrid systems combining fuzzy logic, neural networks, genetic algorithms and expert systems are proving their effectiveness in a wide variety of real-world problems.

2.5.1. Fuzzy neural networks

Neural networks can be modified to incorporate fuzzy techniques and produce a neural network with improved performance. One approach is to allow the fuzzy neural network to receive and process fuzzy input. Another option is to add layers on the front end of the network to fuzzify crisp input data to the fuzzy neural processing [1]. The fuzzy neuron is a fundamental concept used in many approaches to integrate fuzzy and neural technologies. In networks that map fuzzy input to crisp output, nodes in every layer of the network can have modified neurons. The input vector consists of a set of fuzzy values and the weights connecting the node with nodes in the previous layer also have fuzzy values. Input values and the weights are each represented by membership functions. A modified summation process is used to find the product of the membership functions of the fuzzy inputs and weights and then add the resulting membership functions to obtain another one that represents the integration of weighted fuzzy inputs to the node. A centroid operation on the resultant can then be used to find a crisp value for the output of the node [1].

2.5.2. Genetic algorithms and neural networks

Research and development on hybrid genetic and neural systems has grown dramatically since the late 1980s. Most of the activity has been focused on the exploitation of the advantages of genetic algorithms to improve the design and use of neural networks [20–22]. Most of the published work uses the ability of genetic algorithms to search large, complex spaces to prepare data for neural networks, find initial sets of parameters for training networks, and use genetic and the newer evolutionary techniques to evolve neural network topologies. Another work looks at creative ways to couple neural network modules with genetic algorithms and other problem-solving techniques. Research and development efforts also focus on ways to represent neural networks for easier tuning and design by genetic algorithms, ways to substitute genetic algorithms for neural learning algorithms and opportunities for incorporating new techniques from evolutionary computing [1].

2.5.3. Wavelet and neural networks

Wavelet neural network (WNN) is an approach towards the learning function. Wavelet networks, which combine the wavelet theory and feed-forward neural networks, utilize wavelets as the basis function to construct a network. Wavelet function is a local function and influence the networks output only in some local range. The wavelet neural network shows surprising effectiveness in solving the conventional problems of poor convergence or even divergence encountered in other kinds of neural networks. The WNN consists of three layers: input layer, hidden layer and output layer. The detailed description of the calculation steps of WNN is explained in Ref. [23].

2.5.4. Genetic algorithms and fuzzy logic

Fuzzy and genetic systems operate well in similar environments, including situations involving non-linearities and requiring high levels of performance. Therefore, these two technologies are sometimes alternatives and can be used well in the stand-alone or transformational modes [1]. They also work well as modules in coupled systems. In hybrid systems, fuzzy components provide a clear representation of knowledge as rules or mathematical expressions. The use of membership functions and associated parameters provides flexibility and abstraction that simplifies the design of highly complex systems. Genetic algorithms facilitate the optimization of fuzzy system performance. In fuzzy system design, genetic algorithms can be used to tune membership values, prune membership functions and derive fuzzy rules. Fuzzy logic control can be applied to the operation of genetic systems and perform the evaluation function required in genetic algorithms. A less-explored area of integration is the use of the two technologies to produce systems with more general learning abilities such as the semantic interpretation of symbols and the understanding of system behavior from their input and output data [1].

3. Sizing of photovoltaic systems

In the design of stand-alone renewable energy power systems, the optimal sizing is an important and challenging task as the coordination among renewable energy resources, generators, energy storage and loads is very complicated.

A stand-alone photovoltaic power system consists of a photovoltaic array, a storage component, control and power processing components. The PV-array converts sun light into dc electricity. The array is made up of interconnected PV modules. The storage component (usually batteries) stores the electrical energy for use when needed. The control components manage the operation of the system. They may include a tracker to point the PV-array towards the sun to improve energy collection. The power processor converts the dc output of the photovoltaic array into a form needed by the user. PV-hybrid systems couple photovoltaics, controls, power processing and storage with an engine-generator. Other renewable energy generating sources (e.g., wind) can also be included in PV-hybrid systems. PV-hybrids can be configured to reduce energy storage requirements, to provide uninterruptible power for long periods of severe weather, or to operate larger intermittent loads with smaller PV-arrays.

In all cases, engine-generator null time is reduced and the engine can run at maximum efficiency, reducing fuel consumption and maintenance. Controls to coordinate the renewable energy sources, engine-generator and storage components of the system are necessary. Grid-connected systems operate in conjunction with utility generated electricity. For these systems, the utility grid provides both the storage and the alternate power source for the system. These systems require a dc–ac inverter, which provides ac output compatible with utility power quality requirements.

4. Application of AI-techniques for sizing PV-systems

The conventional methodology (empirical, analytical, numerical, hybrid, etc.) for sizing PV-systems have been used generally for locations where the required weather data (irradiation, temperature, humidity, clearness index, wind speed, etc.) and the information concerning the site where we want to implement the PV system are available. In this case, these methods present a good solution, particularly the hybrid method, for sizing PV-systems. However, these techniques could not be used for sizing PV systems in remote areas, where the required data are not available, especially solar radiation. In all of these, accuracy is achieved by using data from daily global irradiation series.

Moreover, the majority of alternative approaches need long-term meteorological data such as total solar irradiation, air temperature, wind speed, etc. for its operation. So, when the relevant meteorological data are not available, these methods cannot be used, especially in isolated areas. In order to overcome this situation, methods that are more recent have been developed for sizing the parameters for PV-systems based on AI-techniques [24]. This section deals with an overview of the application of AI-techniques in PV-systems sizing.

Table 1 summarizes several representative examples of the use of AI in sizing PV systems, which are analyzed in this paper.

Table 1
Summary of numbers of applications presented in sizing photovoltaic systems

AI-technique	Area	Number of applications
Neural networks	Sizing of stand-alone PV-systems Identification of the optimal parameter of PV-system	8
Wavelet and neural network	Sizing of stand-alone PV-systems	1
Genetic algorithm	Sizing of hybrid system Stand-alone wind-generator system Optimization of control strategies for stand-alone Optimal allocation and sizing for profitability and voltage enhancement of PV systems	11
Neural network, neuro-fuzzy and genetic algorithm	Sizing of stand-alone PV system in isolated area	2

Table 2
Summary of applications of artificial neural networks in sizing of PV systems

Number	Authors	References	Year	Subject
1	Mellit et al.	[25,31]	2007, 2003	Application of an adaptive ANN for sizing PV system in isolated area
2	Hontoria et al.	[26,27]	2005	Application of recurrent neural network for sizing of stand-alone PV-system
3	Mellit et al.	[28–30]	2004, 2005, 2007	Application of various ANN architectures for the prediction and identification of the optimal parameters of PV-systems
4	Ohsawa, et al.	[32]	1993	Application of ANN for optimal operation of photovoltaic/diesel

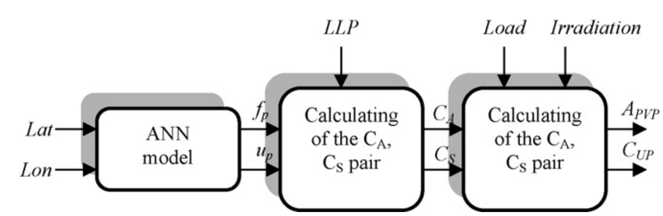

Fig. 1. Flowchart for estimating of the sizing parameters based on MLP [25].

4.1. Application of neural networks for sizing stand-alone PV systems

Table 2 shows a summary of applications of artificial neural networks for sizing PV systems. Mellit et al. [25] developed an ANN model for the estimation of the sizing parameters of stand-alone PV-systems. In this model, the inputs are the latitude and longitude of the site, while the outputs are two hybrid-sizing parameters (f, u). These parameters allow the designers of PV-systems to determine the number of solar PV modules and the storage capacity of the batteries necessary to satisfy a given consumption. Fig. 1 shows the block diagram for this model. Table 3 presents a comparison between calculated (by using hybrid-sizing method) and estimated sizing parameters f and u (by using MLP). According to this table, we can conclude that the relative error does not exceed 6%.

Hontoria et al. [26,27] developed a suitable technique for drawing the iso-reliability curves by using a simplified recurrent neural network. This technique has been applied for Spanish locations. Fig. 2 presents the architecture used for this simulation. Fig. 3 shows an example of generated curve by MLP, for a location Santander, for LLP = 0.01.

In addition, radial basis function network has been used for identification of the sizing parameters of PV-system [28]. Fig. 4 presents the block diagram of the proposed identification method based on RBFN for sizing PV-system.

Fig. 5 shows a comparison between calculated and estimated sizing parameters by RBFN for 16 sites, the LLP is 0.01 and the load is 1 kWh.

Several AI-based methods for sizing PV systems have been developed by the authors in order to select the optimal size of parameters of PV systems in remote areas [29–31]. The results obtained have been compared and tested with experimental

Table 3
Comparison between actual and predicted results [25]

Sites		Sizing parameters data PV system (measured and predicted), LLP = 1%, load = 1 kWh/day					
Lat (°)	Lon (°)	f_m	f_p	Er (%)	u_m	u_p	Er (%)
25	4	1.273	1.232	3.32	0.213	0.221	3.75
29	−6	0.945	0.923	2.38	0.123	0.115	3.95
29	7.5	0.911	0.963	5.70	0.142	0.150	5.63
21	4	0.521	0.491	6.10	0.213	0.201	5.97

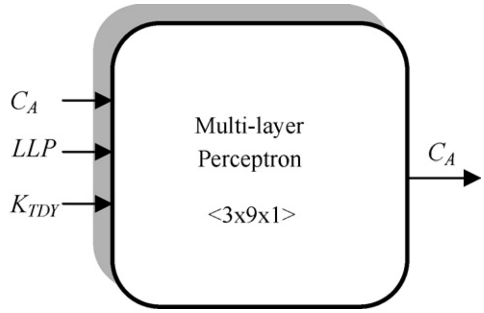

Fig. 2. MLP architecture for the obtaining of the LLP curves [26].

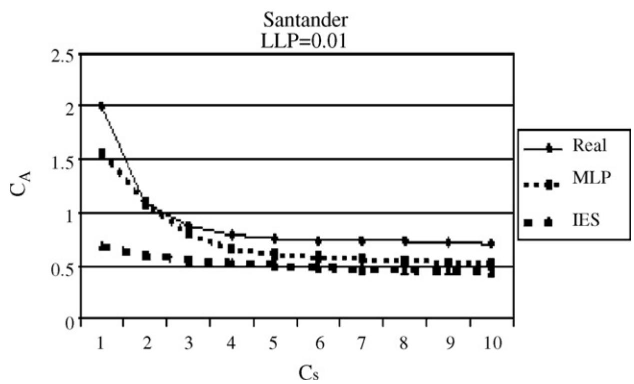

Fig. 3. LLP curves obtained by different methods (Location Santander, LLP = 0.01). IES stands for Instituto de Energia of Madrid method [26].

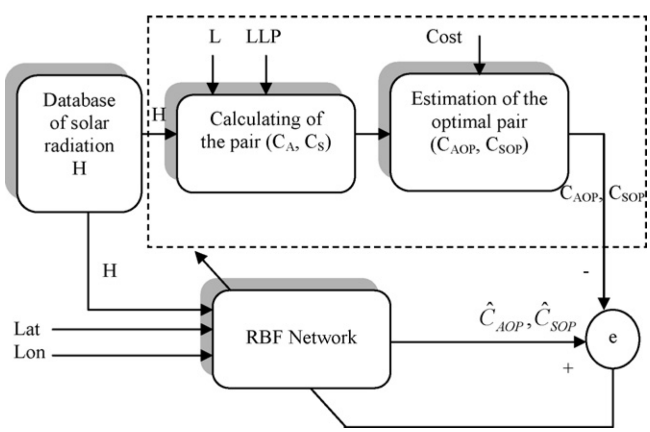

Fig. 4. Block diagram of the identification method based on RBFN [28].

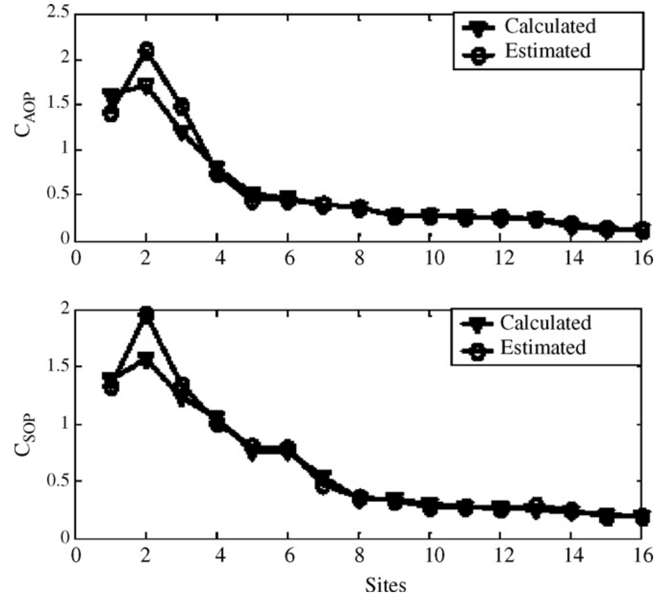

Fig. 5. Comparison between calculated and estimated sizing parameters by using RBFN for 16-points [28].

values. Fig. 6 shows an adaptive ANN for prediction the optimal coefficient of sizing a PV-system.

Fig. 7 shows a nomograph for the sizing of SAPV system, which has been developed corresponding to 10 isolated sites. From this graph, the users of PV systems can determine the PV-array area and the useful accumulator capacity of the battery based on system load demand. This nomograph has been developed based on the proposed RBF-IIR model [31]. Obtained results refer to Algerian sites, but the methodology can be applied to any geographical area in the world.

Ohsawa et al. [32] applied an artificial neural network to the operation control of PV-diesel systems PV-array area.

4.2. Application of genetic algorithms for sizing hybrid PV systems

Table 4 summarizes various applications of genetic algorithms for sizing hybrid PV systems.

Yokoyama et al. [33] proposed a multi-objective optimal unit sizing of hybrid power generation systems utilizing photovoltaic and wind energy. Seeling-Hochmuth [34] presented an article about the optimization of PV-hybrid energy

Table 4
Summary of applications of GAs for sizing of hybrid PV systems

Number	Authors	References	Year	Subject
1	Dufo-Lopez et al.	[37]	2007	Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage
3	Senjyua et al.	[35]	2007	Optimal configuration of power generating systems
4	Koutroulis et al.	[36]	2006	Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems
5	El-Hefnawi S.H.	[38]	1998	Sizing of hybrid system based on GA
7	Yokoyama et al.	[33]	1992	Multiobjectif optimal uinit for Hybrid PV-system
8	Seeling-Hochmuth G.C.	[34]	1998	Optimisation of hybrid energy systems sizing and operation control
9	Dufo-Lopez and Bernal-Agustin	[39]	2005	Design and control strategies of PV-diesel systems using genetic algorithms
10	Xu et al.	[40]	2006	Graph-Based Ant System for Optimal Sizing of stand-alone Hybrid Wind/PV Power Systems
11	Xu et al.	[42]	2005	Optimal sizing of stand-alone hybrid wind/PV power systems using genetic

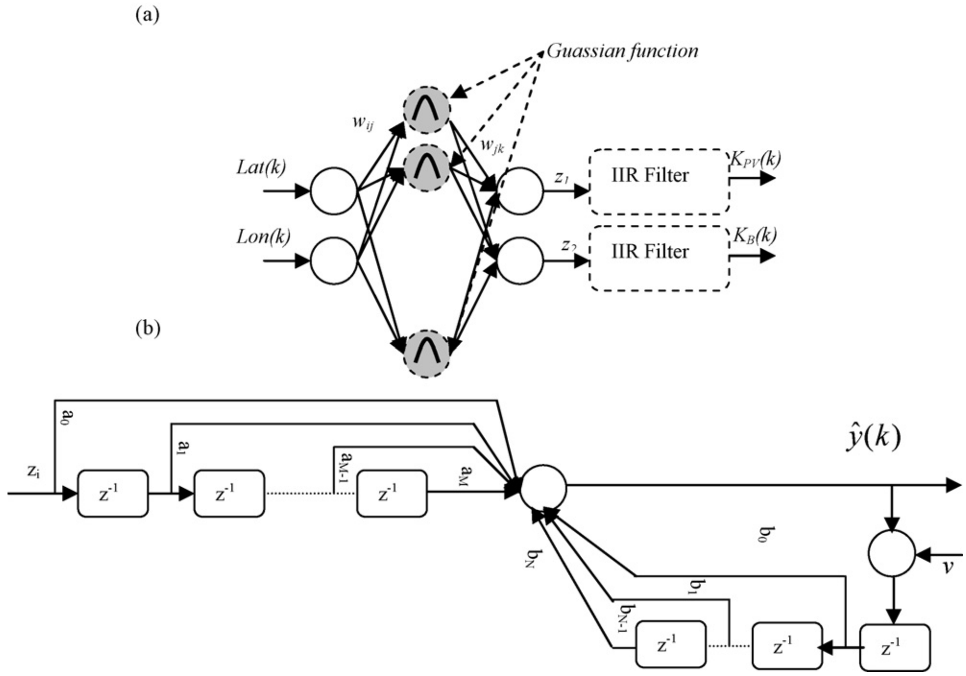

Fig. 6. Adaptive neural network: (a) RBF network architecture; (b) IIR model [31].

systems. The program described optimizes the configuration of the system and the control strategy by means of a GA. The control of the system is coded as a vector whose components are five decision variables for every hour of the year. It is not clear how the optimal vector would be implemented physically in the system, and how the variation of weather would change the running of the system. Well-defined dispatch strategies would be easier to implement physically. The hybrid control algorithm is very simple, where the state of charge (SOC) set point is the only parameter considered. Since there is no detailed description of the GA, with the results being compared with those of a simulation program (HYBRID2), this work can be considered to be in the area of simulations and not in optimization of hybrid systems.

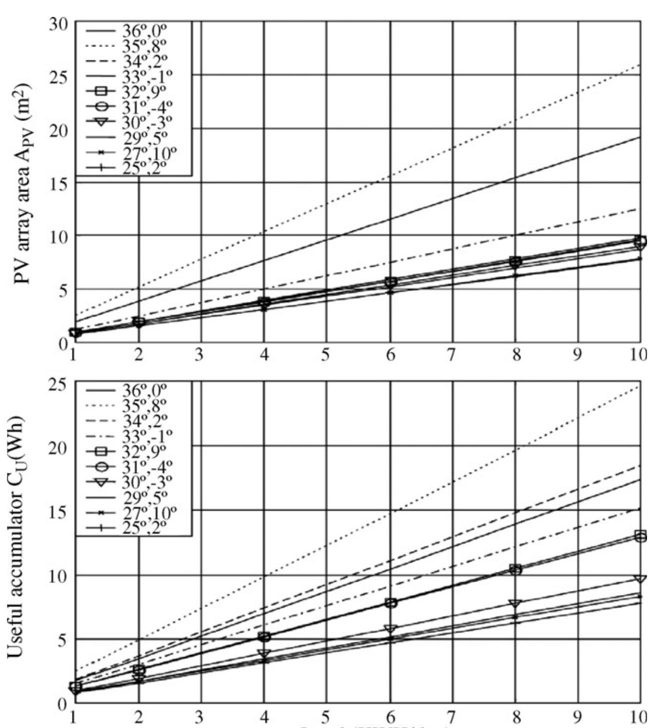

Fig. 7. Nomograph for sizing PV system (from 1 to 10 kWh/day) [31].

Senjyua et al. [35] developed an optimal configuration of power generating systems in isolated islands with RE using a genetic algorithm (GA). This methodology can be used to determine the optimum number of solar array panels, wind turbine generators and battery configurations. The generating system consists of diesel generators, wind turbine generators, PV system and batteries. Using the proposed method, operation cost can be reduced by about 10% in comparison with diesel generators only. Fig. 8 shows the flow chart for the optimal configuration.

A methodology for the optimal sizing of a stand-alone PV/wind-generator systems was developed by Koutroulis et al. [36] in which the proposed methodology is based on the GA and compared with linear programming. The flowchart of the proposed optimization methodology is shown in Fig. 9. The simulation results verify that hybrid PV/wind-generator systems feature lower system cost as compared to the cases where either exclusively the wind-generator or exclusively the PV sources are used.

A novel strategy, optimized by genetic algorithms, to control stand-alone hybrid renewable electrical systems with hydrogen storage is presented in [37]. The optimized hybrid system is composed of RE resources (wind, PV and hydro), batteries, fuel cell, AC generator and electrolyzer.

El-Hefnawi [38] presented a method to design PV-diesel systems. The optimization procedure starts by the definition of

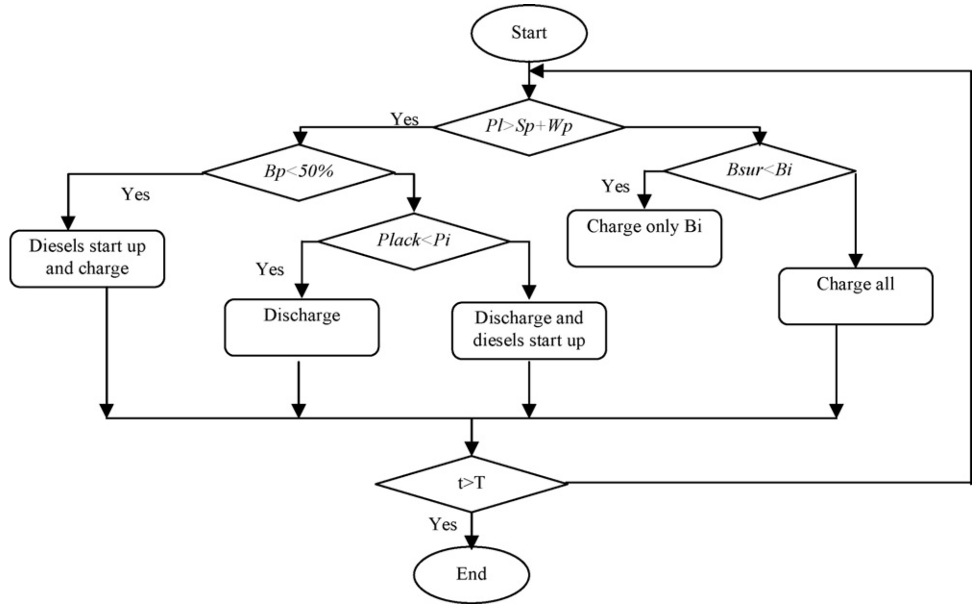

Fig. 8. Flowchart for the optimal configuration [35].

a model of the diesel generator and then optimizes the PV and battery sizes, to determine the minimum number of storage days and the minimum PV-array area.

Lopez and Agustin [39] developed the HOGA (hybrid optimization by genetic algorithms), a program that uses a genetic algorithm (GA) to design a PV-diesel system (sizing and operation control of a PV-diesel system). The program has been developed in C++. A PV-diesel system optimized by HOGA is compared with a stand-alone PV-only system that has been dimensioned using a classical design method based on the

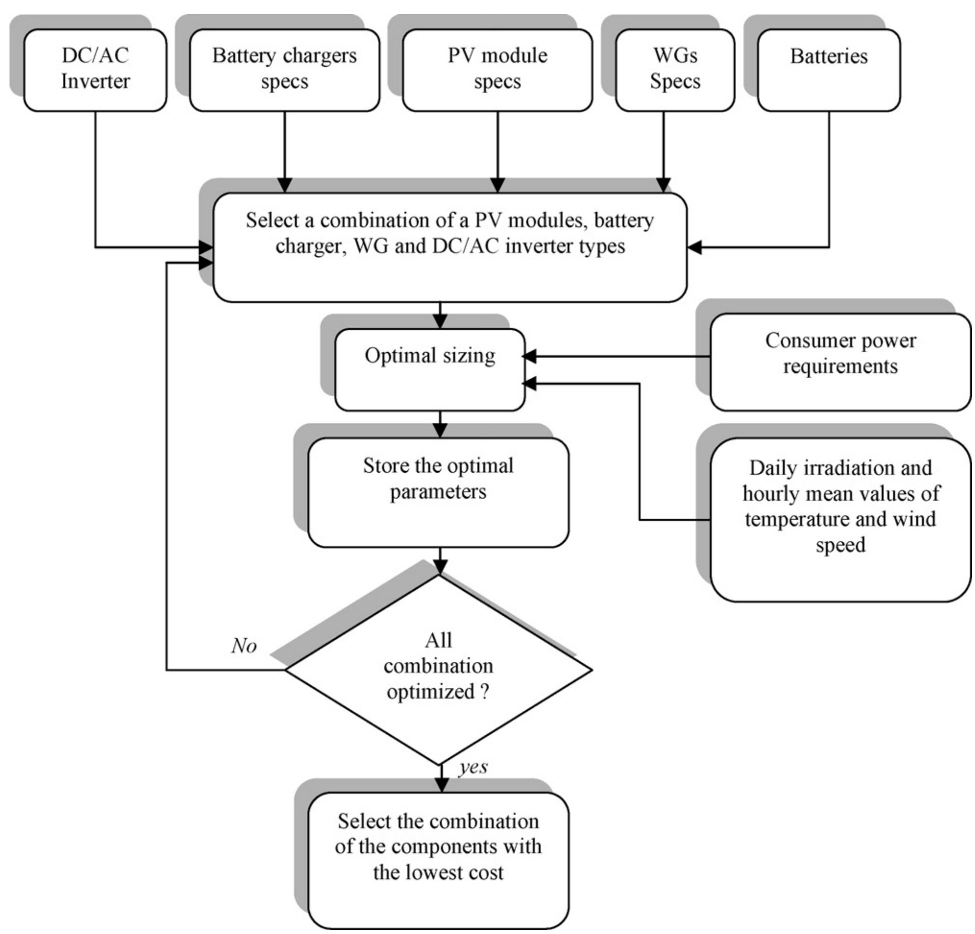

Fig. 9. Flowchart of the proposed optimization methodology [36].

available energy under worst-case conditions. In both cases, the demand and the solar irradiation are the same. The computational results show the economical advantages of the PV-hybrid system. HOGA is also compared with a commercial program for optimization of hybrid systems. Fig. 10 shows the flowchart of HOGA.

Xu et al. [40] proposed a method for sizing of stand-alone hybrid wind/PV power systems, which is formulated as a non-linear integer programming problem. The objective is to select the optimal total capital cost, subject to the constraint of the loss of power supply probability (LPSP) calculated by simulation. A specific graph-based ant system (GBAS) [41] to solve the concerned problem is proposed. A construction graph specifies a particular encoding of the solutions as it runs. The specific graph-based ant system converges very well and this can be verified using the tangent method. The configuration of stand-alone hybrid wind/PV power systems is shown in Fig. 11. In this paper, the case that a system has only one type of WTGs (wind turbine generators) is investigated. The loss of power supply probability (LPSP), which is defined in terms of the battery state of charge (SOC), is the power reliability index of a system. The LPSP can be defined as the long-term average fraction of the load that is not supplied by the stand-alone power system. The experimental results reveal that the proposed algorithm is effective and efficient for sizing stand-alone hybrid wind/PV power systems.

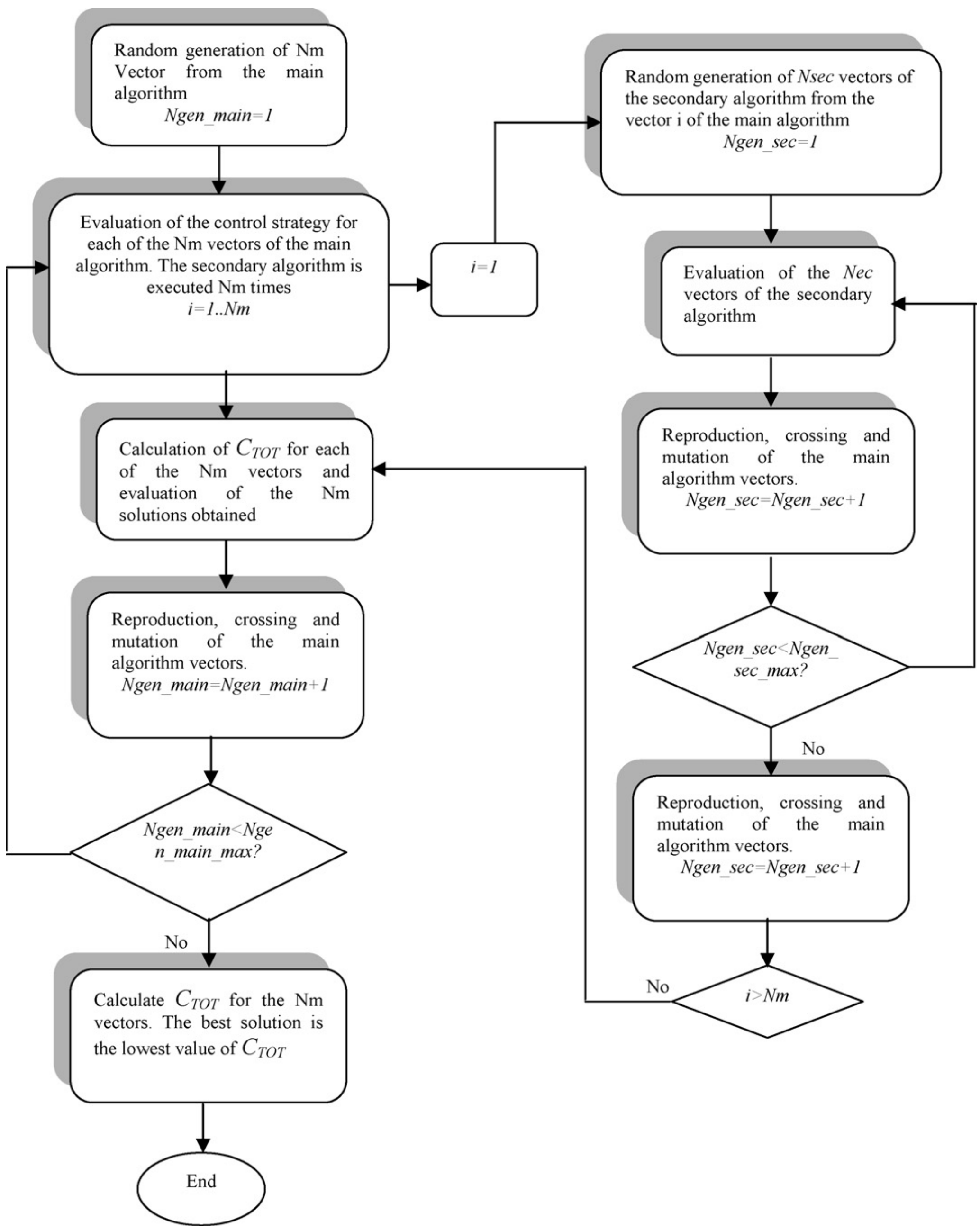

Fig. 10. Flowchart of HOGA [39].

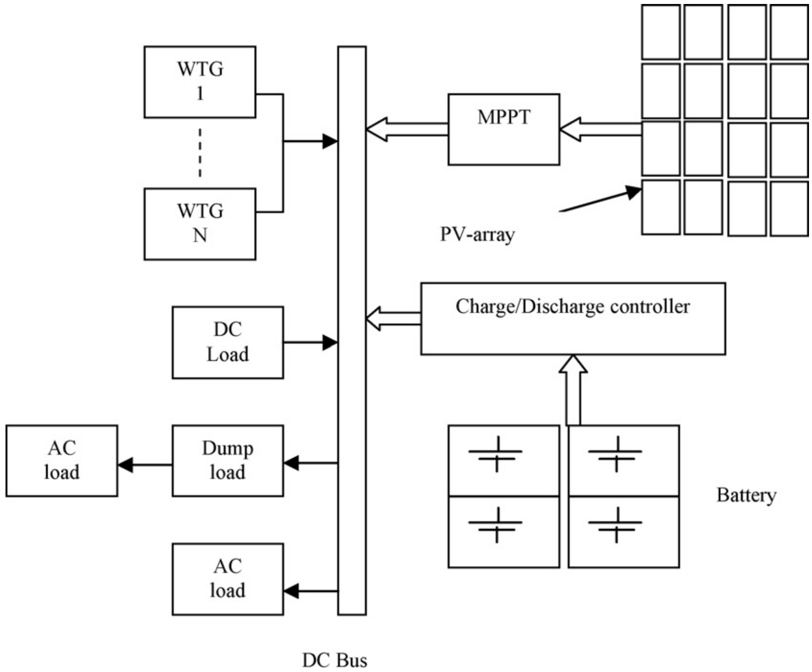

Fig. 11. Schematic diagram of a stand-alone hybrid wind/PV power system [40].

In Ref. [42] the authors investigated the use of a genetic algorithm (GA) with elitist strategy for optimally sizing a stand-alone hybrid wind/PV power system. The objective is to obtain the minimization of the total capital cost, subject to the constraint of the loss of power supply probability (LPSP). The LPSP of every individual of the GA's population is calculated by simulation of all 8760 h of a year. According to the authors, the genetic algorithm converges very well and the methodology proposed is feasible for optimally sizing stand-alone hybrid wind/PV power systems.

4.3. Application of genetic algorithms for sizing grid-connected PV-system

Hernadeza et al. [43] presented a systematic algorithm to determine the optimal allocation and sizing of photovoltaic grid-connected systems (PVGCSs) in feeders that provides the best overall impact onto the feeder. The optimal solution is reached by multi-objective optimization approach. According to the authors, the results obtained with the proposed methodology for feeders found in the literature demonstrate its applicability. The method has been used to test alternative PVGCSs allocation solutions. Simulations in actual feeders prove that the allocation based on the stability voltage distribution achieves the best results. This outcome allows a significant reduction of computation involved in future analysis.

4.4. Application of genetic algorithms for sizing hydrogen PV system

Richardasa and Conibeerb [44] compared the performance of three different solar based technologies for a stand-alone power supply (SAPS) using different methods to address the seasonal variability of solar insolation—(i) photovoltaic (PV) panels with battery storage; (ii) PV panels with electrolyser and hydrogen (H_2) storage; and (iii) photoelectrolytic (PE) dissociation of water for H_2 generation and storage.

4.5. Application of neural networks, neuro-fuzzy and genetic algorithm for sizing stand-alone PV systems

Table 5 shows two applications of neural network, neuro-fuzzy and genetic algorithm for sizing of stand-alone PV system. Genetic algorithm and neural networks have been used to determine the optimal sizing parameters in isolated areas in Algeria [45]. Firstly, the GA has been used to optimize the sizing parameters relative to 40-sites in Algeria and the ANN has been used to predict the optimal parameters in remote areas. Fig. 12 shows the flow chart for the GA process and neural network architecture used for estimating the sizing parameters of a PV-system.

The results obtained by different AI-techniques have been compared and analyzed by Mellit [46]. It should be noted that the proposed hybrid model, which combines ANFIS and GA, presents more accurate results compared to alternative ANNs. The flowchart of the proposed optimization technique based on ANFIS and GA is presented in Fig. 13.

4.6. Application of neuro-fuzzy and wavelet for sizing PV-systems

Table 6 summarizes the applications of neuro-fuzzy and wavelet for sizing stand-alone PV systems. A hybrid model for determining the optimal sizing parameters of PV-system is

Table 5
Summary of applications of neural network, neuro-fuzzy and genetic algorithm for sizing of stand-alone PV systems

Number	Authors	References	Year	Subject
1	Mellit and Kalogirou	[45]	2006	Application of neural network and genetic algorithm for sizing of stand-alone PV system
2	Mellit	[46]	2007	Application of neuro-fuzzy and genetic algorithm for sizing of stand-alone PV-system

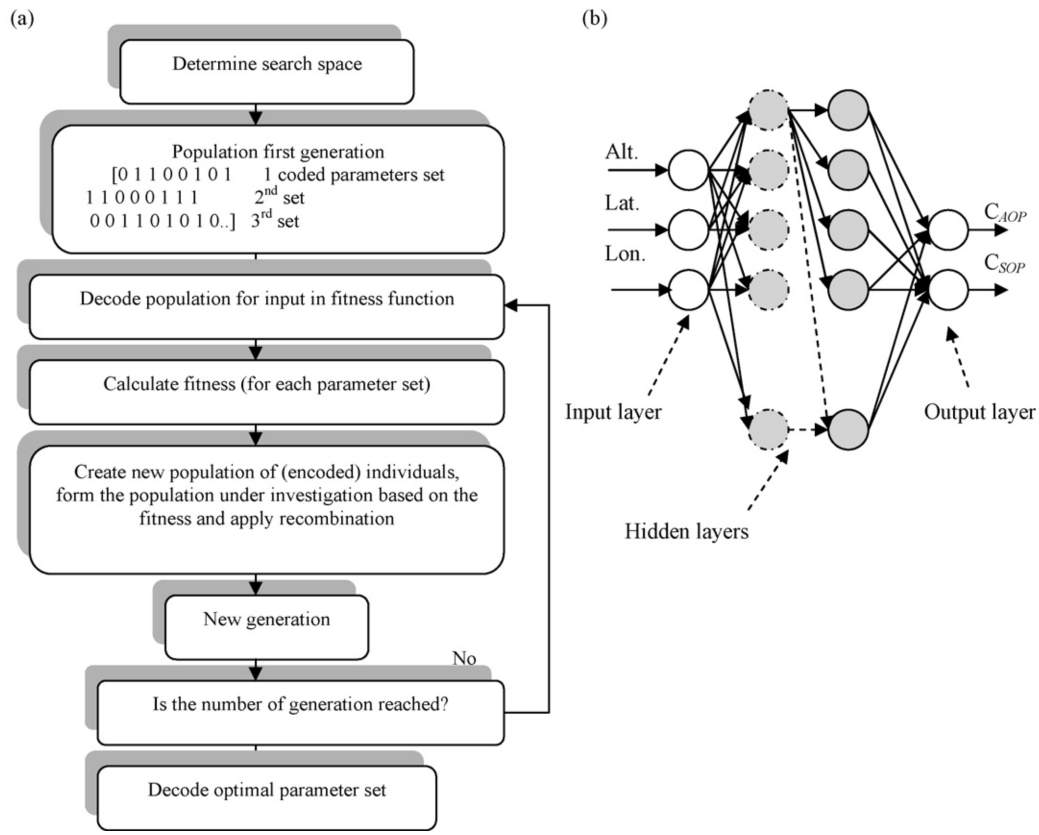

Fig. 12. (a) GA process; (b) ANN architecture used for estimating the optimal sizing parameters [45].

developed by Mellit [47], which combines a neural network and fuzzy logic, called neuro-fuzzy. It can be used for predicting the optimal sizing coefficient of PV-systems based only on the geographical coordinates. Fig. 14 shows the architecture used for sizing of PV-systems.

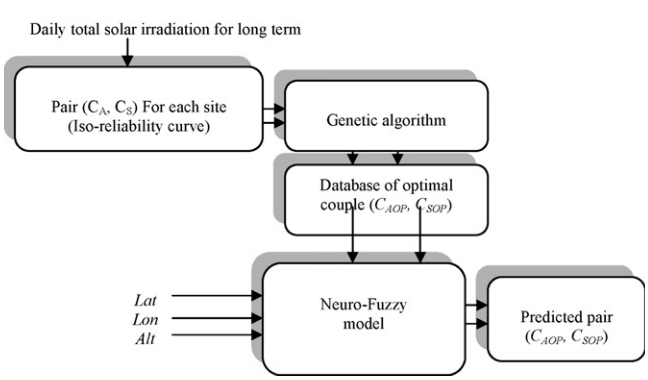

Fig. 13. Flowchart of the proposed optimization technique based on ANFIS and GA [46].

A comparison between different ANNs architectures and the proposed ANFIS for estimating the sizing parameters are presented in Fig. 15.

Mellit et al. [48] developed a suitable approach, which combines the ANN with wavelet analysis for the sizing of stand-alone PV system. The proposed approach presents more accurate results compared with MLP, RBF and RNN. Fig. 16 shows the ANN-wavelet architecture employed for sizing PV-systems.

Table 6
Summary of applications of neuro-fuzzy and wavelet for sizing of stand-alone PV systems

Number	Authors	References	Year	Subject
1	Mellit A.	[47]	2006	Application of an ANFIS for sizing of stand-alone PV system
2	Mellit et al.	[48]	2004	Application of neural network and wavelet for sizing of stand-alone PV-system

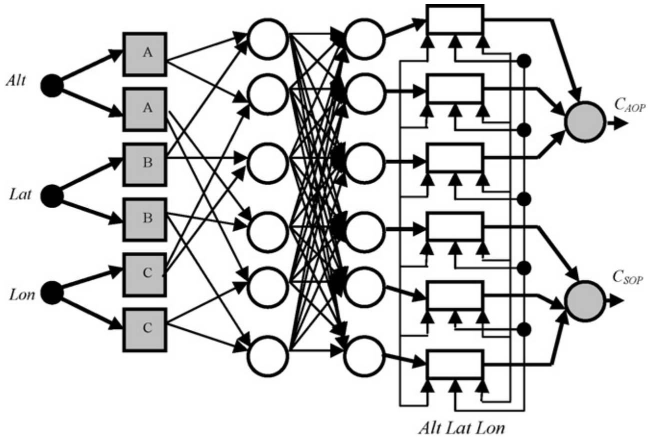

Fig. 14. ANFIS-based sizing of PV-system [47].

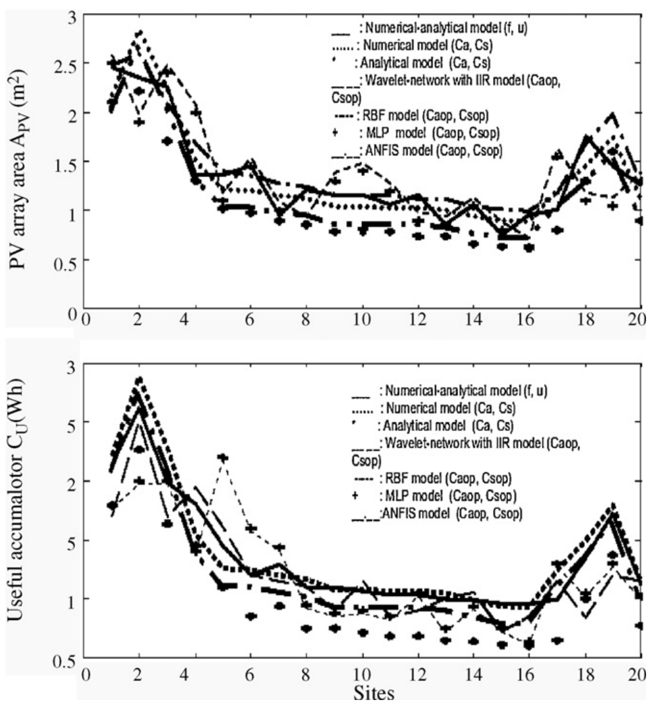

Fig. 15. Comparison between analytical, numerical, hybrid model, ANNs and the ANFIS architecture for estimating the PV-array area and the useful capacity in 20-locations for Algeria [47].

5. Conclusions

In this paper, various AI-techniques used for sizing stand-alone, grid-connected and PV-hybrid PV systems, have been reviewed. Conventional sizing methods such as empirical, numerical, analytical and hybrid present a good solution, when all required data are available (meteorological data, information concerning the sites, etc.). However, in cases where these data are not available, the conventional techniques could not be used. However, these methods should not be disregarded totally, since the new proposed AI-techniques for sizing PV systems are based mainly on the conventional methods such as the hybrid-sizing techniques.

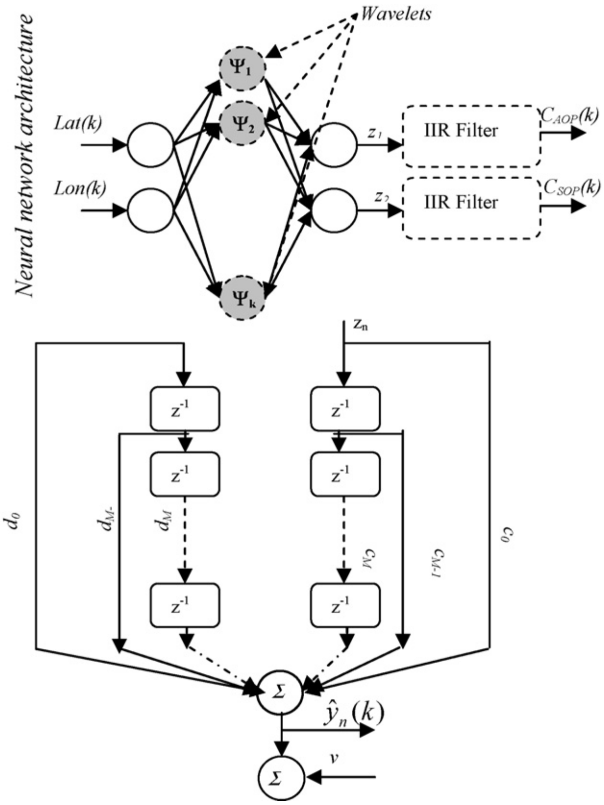

Fig. 16. ANN-wavelet for sizing PV-system [48].

According to these applications, the importance of the using AI for the sizing of PV-systems should be noted. AI-techniques have demonstrated the possibility for sizing PV-systems successfully and with reasonable accuracy.

Generally, AI-techniques have demonstrated the possibility for sizing PV-systems based on some available data successfully and with reasonable accuracy. Published literature on the sizing of PV-systems based on AI-techniques indicates their popularity, particularly in isolated areas. This shows the potential of AI as a design tool in the optimal sizing of PV systems.

The number of applications presented here is neither complete nor exhaustive, but merely a sample of applications that demonstrate the usefulness and possible applications of AI-techniques. AI-based sizing of PV systems has been applied in many countries such as Algeria, Spain, Greece, Ireland, Island and Turkey.

Thus based on the review work presented here, AI-techniques seem to offer an alternative method for sizing PV-systems in many regions of the world that lacks complete data.

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